Neural network analysis of musculoskeletal responses to electrical AC-stimulus

M. Hannula[1], E. Alasaarela[2] , J. Laitinen[1]
[1]Institute of Technology, Oulu Polytechnic, Oulu, Finland
[2]Department of Electrical Engineering, University of Oulu, Oulu, Finland

Abstract - **Analyzing the human body by the application of alternating electrical currents is not a widely known method in medicine. In our research, we stimulated test persons by exposing them to different low frequencies and measured their responses to them. This method, known as FAM (Frequency Analysis Method), can be used to estimate the physiological condition of patients. In this study, we present a method of processing the results using neural networks. By producing user-friendly visual data, the processing method aids a physiotherapist in the interpretation of the results, resulting in a more reliable diagnosis.**
***Keywords* - Physiotherapy, biomedical engineering, neural networks, physiological condition, frequency analysis method, FAM, SOM**

I. INTRODUCTION

Various kinds of electrical measurements have been used to investigate the human body, including the mechanical or chemical stimulation of organs and tissues. Stimulation by continuous wave alternating electrical currents, however, is not a widely used method, although the body itself, and especially the central nervous system, employs electrical currents and impulses. A novel method known as FAM (Frequency Analysis Method) was invented in Oulu [1] to evaluate the physiological condition of the human body, musculoskeletal disorders in particular.

In the Frequency Analysis Method, an alternating current is fed into a patient’s wrists, ankles and back at a selected frequency. The current's intensity is increased incrementally and the patient's responses are registered as thresholds of sensory, motoric and pain reactions. Repeating the procedure at several frequencies (10 – 100 Hz) produces a set of FAM data, capable of providing a wealth of information concerning the patients’ physiological condition.

This paper presents an analysis method for FAM data by means of artificial neural networks utilizing Self-Organizing Maps (SOMs) [2]. To test the method, FAM data from 96 test persons were organized using a selected SOM.

Neural networks are widely used in biomedical applications. For example, they have been proposed for the automatic detection of microcalcification clusters in mammograms [3]. In addition, neural networks can be used to support medical decision-making by combining qualitative and quantitative medical knowledge [4]. Our application is based on using a SOM neural network to categorize FAM data by comparing it to previous data and interpretations.

II. METHODOLOGY

A. The measurement

Using the following procedure, the FAM data in our measurements were obtained from five points; namely, the patients' wrists, ankles and back.

The electrodes of an IF Electrotherapy unit [5] were attached to the measurement location, and a physiotherapist switched on an alternating current starting at the A Hz frequency at the current level of 0 mA. Then, the therapist increased the current incrementally and monitored the responses of the patient, documenting thresholds of sensory, motoric and pain reactions in terms of current values. The definitions of these reactions were agreed on in advance. By repeating the process at varying frequencies (in the experiments of the present paper A = 10 Hz, B = 50 Hz and C = 100 Hz) in each measurement location (both wrists, ankles and the back) provides a full set of FAM data for the patient.

Table 1 shows FAM data measured from a patient's limb.

TABLE 1
EXAMPLE OF FAM DATA

	A Hz	B Hz	C Hz
Sensory	11mA	12mA	14mA
Motoric	12mA	14mA	15mA
Pain	30mA	30mA	30mA

Current values in the different columns reveal the patient's specific reactions to AC stimulation. The first value, 11mA, defines the person's sensory threshold at A Hz, and represents the person's “first feeling of the current”. The motoric threshold is the point where the limb begins to react by mechanical vibrations. The pain level represents the value at which the patient experiences physical pain.

B. Expert analysis of the measurements

A physiotherapist who is experienced in the FAM method can experimentally analyze FAM data quite accurately and give a correct diagnosis. However, as the FAM is a new and relatively unknown method, no reference values exist for the measurements. The measurements typically produce nine or more current values for each limb, rendering the definition of reference values very hard by means of simple statistical methods. Thus, a wider utilization of the method necessitates an improved numerical analysis method.

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C. The new analysis method

To study the analysis of FAM data, 96 test persons were measured, and medical experts diagnosed them into four classes (healthy, fibromyalgic, back pain, neck pain). Table 2 shows the characteristics of the data.

TABLE 2
CHARACTERISTICS OF THE DATA

Subjects	96
Measurements total	224
Distribution of measurements:	
Right hand	67
Left hand	39
Right leg	75
Left leg	17
Back	26
Diagnoses	
Healthy	96
Fibromyalgic	28
Back pain	80
Neck pain	20

As the table indicates, not all test persons were measured at every location. That is a standard procedure in the FAM method and is natural, because, for example, it is rarely relevant to attempt to analyze the condition of a patient's leg on the basis of hand measurements. However, the fact that data from some measurement locations is missing makes the analysis more demanding. Still, the method should be able to produce reliable results from sparse data.

To obtain maximum benefit from a FAM analysis in a physiotherapeutical investigation, the interpretation of the results should be clear and well-motivated to enable the integration of the results with expert knowledge.

These reasons led to the idea of using Self-Organizing Maps (SOMs) in the analysis of FAM data [2]. SOMs have the advantage that they enable both analysis of and datamining in such data where the important factors are not generally well known.

Preprocessing

The data were preprocessed to an appropriate form bearing in mind two specific considerations. First, the data were processed such that possible associations with expert knowledge relating to the FAM data could be easily handled and the data could be properly fed to the SOM. The second consideration involved the selection of preprocessing method for the easy utilization of the data also in the absence of some values.

With this in mind, the FAM data were preprocessed using first order curve fitting. A FAM data matrix (Table 1) was fitted to the current both as a function of frequency and of reaction threshold (using the following indices 1=sensoric, 2=motoric, 3=pain). As a result of curve fitting, the FAM measurement can be expressed as

$$I(react\_th) = k_{react\_th} \times react\_th + b_{react\_th} \qquad (1)$$

$$I(frequency) = k_{freq} \times frequency + b_{freq} \qquad (2).$$

Equations 1 and 2 allow the responses of each current value to be studied either as a function of frequency or of reaction threshold. This is helpful in the physiological interpretation of the FAM data. In addition, such fitting enables the utilization of incomplete data.

A FAM analysis allows measurements also at other frequencies and reaction thresholds than those used in this study. The same parameters can be extracted from FAM data using fitted functions, despite varying measuring frequencies or reaction thresholds. This is useful, because the measuring frequencies of the FAM method have not been fixed yet.

The data was preprocessed using functions (1) and (2), and the fit of the errors was $0 \pm 2.3mA$ (mean $\pm$ SD) for function (1) and $0 \pm 1.3mA$ (mean $\pm$ SD) for function (2). As the error level was relatively low (the measuring interval was 1 mA), the preprocessing method was assumed to be sufficiently accurate for parameterizing FAM data.

Neural network analysis

A Self-Organizing Map (SOM) defines mapping from the input data onto a two-dimensional array of nodes. Every node is associated with a reference vector $m_i = [\mu_{i1}, \mu_{i2}, ..., \mu_{in}]^T$. The nodes are arranged to a hexagonal lattice for visualization purposes. An input vector $x = [\xi_1, \xi_2, ..., \xi_n]$ is connected to all neurons in parallel via variable scalar weights μ_{ij}. So, the input *x* is compared in parallel to all the nodes m_i and the location of the best match is defined as the location of the response.

The basic algorithm for the self-organization of the weight vectors has the form [2]

$$m_i(t+1) = m_i(t) + h_{ci}(t)[x(t) - m_i(t)] \qquad (3)$$

where $h_{ci}(t)$ is a neighborhood function,
$m_i(t)$ is a weight vector *i* in the SOM
$x(t)$ is a training example and
t=0, 1, 2, ... is a discrete-time index.

The result of a SOM that has been taught using algorithm (3) can be evaluated by defining the average expected distortion measure (4) [2].

$$E = \int \sum_i h_{ci} f\left(d\left(x, m_i\right)\right) p(x) dx \qquad (4)$$

where

$d\left(x, m_i\right)$ is the quantification error, i.e., the distance between x and m

$p(x)$ is the probability density function of x.

The result of self-organization is a network with appropriate weights $m_i(t)$, which minimize function (4) for x. Two important considerations entered into the training of the SOM: the quantitative values of the data had to be approximated and smoothly organized. In a very large network, E equals zero, but its generalizability is poor, and vice versa (in a small network the statistical confidence of the weight m_i will be high). Hence, the right result for the SOM is a compromise between the two considerations.

The test persons were classified into four classes (healthy, fibromyalgic, back pain, neck pain). The SOM was trained in the supervised mode, meaning that every diagnosis was included as a parameter in the training data. Finally, the self-organized diagnosis parameters were used in the clustering of the data.

III. Results

To investigate the diagnostic power of the SOM neural network in FAM data processing, a PC-based neural network was built up using Matlab® software and a SOM Toolbox. The FAM data obtained from the wrists of the 96 test persons are presented in this report.

The training of the SOM produced a network with reference vectors $m_i = \left[\mu_{i1}, \mu_{i2}, ..., \mu_{i15}\right]^T$. The first 12 dimensions define the reference vector for the parameters of the FAM data. The last 3 dimensions define the reference vector for the diagnosis parameters.

The resulting SOM can be visually interpreted such that the last three dimensions of the reference vector m_i are compared to each other and the highest value is declared the winner. This produces one diagnosis index per every node in the SOM. The indices can be expressed visually as coloured areas, as illustrated in Fig. 1.

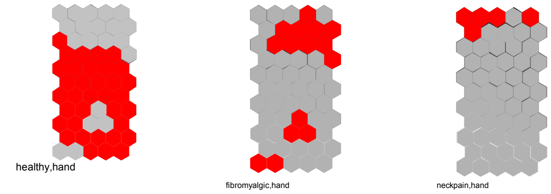

Fig. 1. Diagnosis areas in hand measurements for healthy, fibromyalgia and neck pain subjects.

Fig. 1 shows that FAM data can be clustered by the SOM. Note that the clustering was generated through self-organization, i.e., the groups were formed "naturally".

As discussed earlier, the interpretation of the analysis must be unambiguous. So, the reasons behind clusterization can be understood on the basis of the component planes of the first 12 dimensions of the reference vector m_i, expressing the parameters of the FAM data. Fig. 2 presents the component planes for the dimensions in wrist measurements.

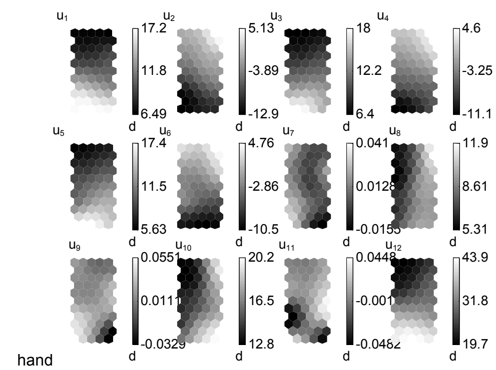

Fig. 2. Component planes of the SOM

The component planes presented in Fig. 2 clearly indicate which parameters differ from those illustrated in Fig. 1.

In practice, the analysis is made by preprocessing the measured FAM values and comparing the 12 FAM parameters with the corresponding dimensions on the reference vectors to produce the best match. Next, a diagnosis index is defined by comparing the last three dimensions of the previously defined best match and selecting the highest index for the final result of the diagnosis. Fig. 3 illustrates the visualization of the results using coloured areas.

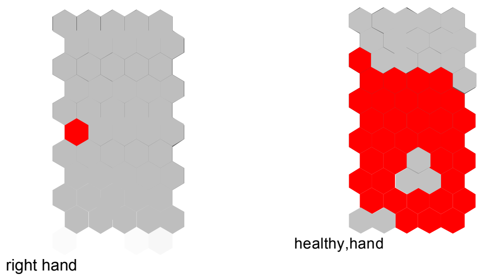

Fig. 3. The measurement (right) and the corresponding diagnosis plane (left)

The data shown in Fig. 3 can be interpreted as representing a healthy person. If more information for the diagnosis is required, the component plane shows the parameters of the measurements. Furthermore, the parameter values can be traced back to the real FAM current values on the SOM plane, which is sometimes useful.

IV. Discussion

The problem with the FAM method was that the interpretation of measurement results was too dependent on the personal judgments of physiotherapists who were familiar with the method. To circumvent this limitation, it was necessary to develop a form of numerical analysis to assist in the final analysis of the results.

FAM measurements can be used to describe the physiological state of the human body. However, the results leave room for interpretation. For example, the coloured area in Fig. 1 indicates fibromyalgia in the middle of a healthy area. This may indicate that the data comes from a healthy person, who has been incorrectly diagnosed with fibromyalgia. Another source of error are invisible factors affecting fibromyalgia. Problems such as these suggest that the current realization of the FAM method is rather limited. As the applied frequencies were selected experimentally, special attention should be paid to developing the parameters to obtain more accurate and reliable results.

The neural network analysis utilizing the self-organization algorithm appeared to be highly suitable for analyzing and interpreting the FAM measurements. Moreover, the reference values (typical values for the different diagnosis groups) can be easily defined on the basis of the component planes of the SOM. Furthermore, a suitable preprocessing method to integrate the SOM analysis and the physiotherapist’s opinion strengthen the final interpretation and analysis of the patient's physiological state.

V. Conclusion

This study shows that FAM measurements provide essential information on the physiological state of the human body and can be analyzed using the proposed method. The method applies Self-Organizing Maps to produce an easily interpretable analysis. The method has potential as a novel basic tool for physiotherapists.

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